REAL-TIME QUALITY CONTROL OF FABRIC BASED ON MULTIVARIATE CONTROL CHARTS

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Abstract

This contribution deals with a procedure of monitoring fabric production process in terms of defect detection. Detection algorithm is based on spectral approach with 2D Fourier transform, which has shown to be suitable method of describing periodic and almost periodic structure of fabrics. Multivariate control charts are used as a tool for monitoring several quality variables. In order to make an off-line and on-line quality monitoring of fabrics possible, we built up a prototype machine, which consists of aluminium frame, DC motor, LED lights and a line scan camera. Fabric width is $50cm$ and maximum winding speed of about $16m/min$ can be achieved. The core of detection algorithm utilizes relatively time consuming Fourier analysis, so we split an acquired image into independent parts and let the work be done concurrently. Writing native, multi-threaded and scalable code, that takes advantage of modern multi-core machines, is one of our main objectives. Based on *Visual C++* language and additional libraries, we are able to to check $1m^2$ of fabric in about 1.5 second on *Intel Core2 Quad CPU*. We use *OpenCV* library together with *Intel Threading Building Blocks* templates for the most part.

1 Introduction

Quality control has gained major importance in today's manufacturing process. In textile industry especially, the monitoring is still performed by human observation. This process involve a group of workers repeatedly checking the product many times again. The human visual inspection makes the final product much more expensive, moreover, such way of control does not achieve more than 70% of all defects to be detected. Goal of our research is to investigate and develop new algorithms for the detection of defect in textured materials (textiles) using automated visual inspection. These algorithms are expected to offer high detection rate with low level of false alarm.

Fabric is, as a rule, composed of two sets of mutually perpendicular and interlaced yarns. The weave pattern of basic unit of the weave is periodically repeated throughout the whole fabric area with the exception of the edges. Due to the periodical nature of woven fabrics, their images are homogeneously structured and can be considered as texture images. Considering the periodic nature of fabric, we are able to describe the relationship between the regular structure of woven fabric in spatial domain and its Fourier spectrum in the frequency domain. The directional feature of periodical structure of woven fabric correspond to high energy frequency component in the Fourier spectrum. Therefore, the Fourier transform seems to be appropriate for graphical representation of planar anisotropy of images in spatial domain, as it is shown *Tunak & Linka (2007)*. A presence of defect in this periodical structure causes changes in periodicity and consequent changes of spectral features.

In his paper, we especially focus on recognition of common directional defects associated with the change of weaving density or defects that appear as a thick place distributed along the width or height of an image. The method will be illustrated by certain examples of analysis of real fabrics with various defects. The basic principle of detection method lies in estimation of periodic characteristics over the entire fabric sequentially by a concept of sliding window. At each step, statistical comparison is performed in order to recognize those parts that contain defects. Multivariate statistical process control is used to make such decision. Other approach, e.g. statistical approach based on second-order statistical features extracted from a grey level co-occurrence matrix for automatic detection of defects in woven fabrics can be found in *Tunak* & *Linka (2008)*.

Aim of the final quality inspection of woven fabric is efficient detection and localisation of defective regions. Multivariate statistical process control as a technique for monitoring of multiple quality variables simultaneously, with the aid of Hotelling's multivariate control charts, is used for automatic detection.

In addition to development of algorithms for defect detection in textiles, we constructed a special laboratory device that allows us to acquire the image of moving fabric. This device, among the other parts, consists of line scan camera, step motor and associated PC that takes care about the control of these devices and that performs overall data processing. In this article, we also explain some fundamental concepts that make the on-line process control possible.

2 Two Dimensional Discrete Fourier Transform

The spectral approach is based on two-dimensional discrete Fourier transform (2D DFT). The Fourier spectrum is ideally suited for describing the directionality of periodic or almost periodic patterns in grey level images of textures. Let $f(x, y)$ be a two-dimensional function, where $x = 0, 1, 2, ..., m - 1$ and $y = 0, 1, 2, ..., n - 1$, are the spatial coordinates and the amplitude f at any pair coordinates is the grey level of the image of size *m* x *n*. The 2D DFT of $f(x, y)$ is given (*Gonzales* & *Woods (2002)*)

$$F(u, v) = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y) e^{-j2\pi(\frac{ux}{m} + \frac{vy}{n})} \tag{1}$$

where $u = 0, 1, 2, ..., m-1$ and $v = 0, 1, 2, ..., n-1$ are frequency variables. The *dc* (direct current) component is the origin of frequency domain $F(0, 0)$ and represents the origin of the system of frequency coordinates. If $f(x, y)$ is real, its transform is, in general, complex. The *power spectrum* is defined as the square of magnitudes

$$P(u, v) = |F(u, v)|^2 \tag{2}$$

In order to display and analyse the *power spectrum* visually, it is convenient to reduce dynamic range of coefficients by *logarithmic transformation*

$$Q(u, v) = log(1 + |F(u, v)|^2) \tag{3}$$

A typical woven fabric consists of two, mutually perpendicular arrays of yarns. The resulting periodic structure can be nicely seen in both an image of spatial domain, even in an image of frequency domain. It is also true, that any defect in weft or warp direction causes serious disorder in such periodic structure, and as a consequence, takes significant effect in distribution of Fourier spectrum coefficients.

3 Anisotropy of Fiber Systems

One of the common operations of image analysis is called a segmentation. The purpose of segmentation is to split the information captured by the image into logical parts that have close relation to objects of a real world. These objects are either randomly distributed on the image background or they prefer certain directional placement. In textile experience, the objects are considered to be fibers, threads and cross-sections of fibers. Complex systems built of these basic objects can be represented by webs, fibre layers, woven fabrics, knitted fabrics, non-woven textiles etc.

In our implementation, we consider a grey scale image to be a square matrix of size *m* x *m*. It is convenient to let *m* be an odd number for correct definition of the center of the Fourier spectrum. All frequency components from the Fourier spectrum are summed in the directional vector of certain angle α. Since the transformation of real image function $f(x, y)$ results in complex coefficients, the absolute magnitudes of frequency components $|F(u, v)|$ are obtained according to relation (**??**). The sum of frequency components S_α in the directional vector is given by

$$S_\alpha = \sum_{i=1}^{(m+1)/2} |F(u, v)|_i \tag{4}$$

where α forms an angle between the directional vector and u axis, $|F(u, v)|$ is a frequency component of the directional vector at the coordinates (u, v) and m is the size of the image. The Bresenham's line algorithm is used to estimate coordinates of corresponding matrix elements.

4 Defect detection

4.1 Multivariate control charts

The objective of our work consists of efficient detection and localization of defective regions in the image of fabric, which is important part of quality control. Because exploring each quality feature individually could lead to inadequate results, we decided to keep track of multiple variables simultaneously. The process of observing several quality features together is known as multivariate statistical process control. Hotelling's multivariate control charts, which are a direct multivariate equivalent of the Shewhart $\overline{X}$ charts (based on Mahalanobis distance) for the process mean, are useful tool that integrates multiple texture features and help judge the presence of defects.

We assume, that the observations come from p-dimensional normal distribution with known mean vector $\boldsymbol{\mu}$ and known variance-covariance matrix $\boldsymbol{\Sigma}$. Then the test statistic D^2 for i-th individual observation has the form (*Bersimis et al. (2007), Zamba* & *Hawkins (2006)*)

$$D_i^2 = (\mathbf{X}_i - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{X}_i - \boldsymbol{\mu}) \tag{5}$$

where $\mathbf{X}_i$ is the i-th, $i = 1, 2, ..., m$, observation that comes from p-dimensional normal distribution $N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. In real situation we often face the problem, that mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$ are not known in advance. Therefore we obtain the data $\mathbf{X}_j$, $j = 1, ..., n$ while the process is in statistical control. We consider these data to be a random sample from a p-dimensional normal distribution $N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, where $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ are unknown. Sample mean and sample variance-covariance matrix of this distribution are defined

$$\overline{\mathbf{X}} = \frac{1}{n} \sum_{j=1}^{n} \mathbf{X}_j \tag{6}$$

$$S = \frac{1}{n-1} \sum_{j=1}^{n} (\mathbf{X}_j - \overline{\mathbf{X}})(\mathbf{X}_j - \overline{\mathbf{X}})^T \tag{7}$$

where $\overline{\mathbf{X}}$ and S are unbiased estimates of $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$. Then the test statistic for an observed vector $\mathbf{X}_i$ is

$$D_i^2 = (\mathbf{X}_i - \overline{\mathbf{X}})^T S^{-1} (\mathbf{X}_i - \overline{\mathbf{X}}) \tag{8}$$

For later process control, that follows the initial calibration of control charts from a "learning sample", we define the upper control limit as

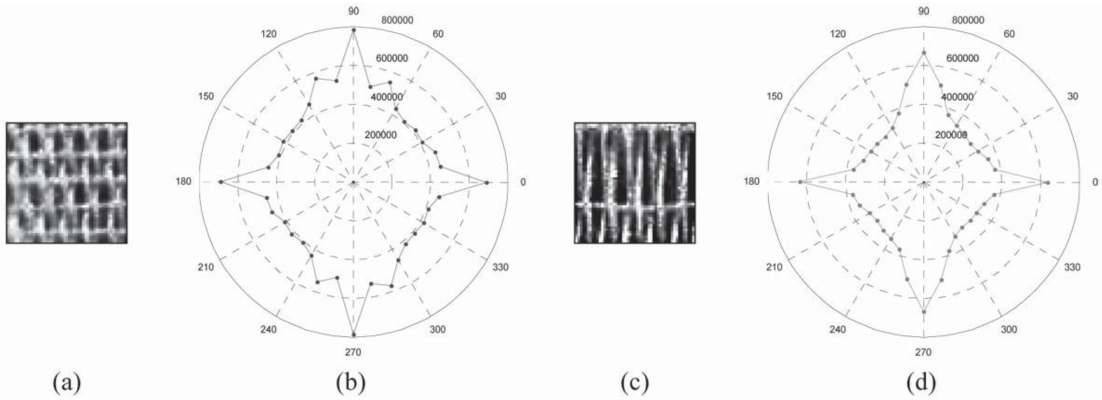


Fig. 1: (a) Window with non-defective area, (c) window with defective area, (b),(d) polar plots of S_α in 10 degree step.

$$UCL = \frac{p(n+1)(n-1)}{n(n-p)} F_{p,n-p}(1-\alpha) \tag{9}$$

where $F_{p,n-p}(1-\alpha)$ is the $(1-\alpha)$ percentile of the F-distribution with p and $(n-p)$ degrees of freedom. In case of D_i^2 statistic exceeds the upper control limit at specified level of significance α, then the observation is considered to be out of control.

4.2 Defect Detection using Multivariate Control Charts

We consider values of S_α obtained from image of fabric as a vector of features $\mathbf{X}_i$. These features can be used for evaluation of material homogeneity and searching for random imperfections in regular structure. Images of the same or identical structure would have similar shape of estimated rose of direction, i.e. almost the same values of S_α. On the other hand, image of structure with defective area would have different shape of polar plot of S_α. This idea, supported by multivariate control charts, can find its application of defect detection inside of a real structure.

Figures 1(a),(c) display windows of 50x50 pixels taken from regular and defective parts of the source image (see Figure 4(g). Corresponding polar plots of S_α with the 10 degree step obtained form equation (9) can be seen in Figure 1(b),(d). Difference in shape of these polar plots is obvious.

At the beginning, values of S_α are captured using 10 degree step over 1000 randomly selected sample windows in a defect free area. As a result we get data matrix with $n = 1000$ samples of $p = 18$-th dimensional normal distribution. Then the upper control limit given by formula (9) for a level of significance $\alpha = 0.001$ is evaluated. Monitoring of fabric area is based on sliding window moving systematically over the whole image area. The step between subsequent windows is half their size so they fully overlap. For every window, i-th test statistic is evaluated using Mahalonobis distance from equation (8). Then the distance is compared with given *UCL*. If any observation exceeds the limit, the window is considered to be at the position of significant defect.

Example in Figure 2(a) represents image of real woven structure containing defect, concretely insufficient weft density. Figure 3(c) shows the plot of *i*-th test statistic against the upper control limit. Result of detection algorithm can be seen in Figure 2(b), where the marker windows represent defective areas. In order to get even better idea, Figure 2(d) shows polar plots of S_α with the step of 10 degrees, where the dark curves represent the windows with regular structure and grey curves highlight the windows where the structure does not match given criteria. Similarity in shape of polar plots can be seen for

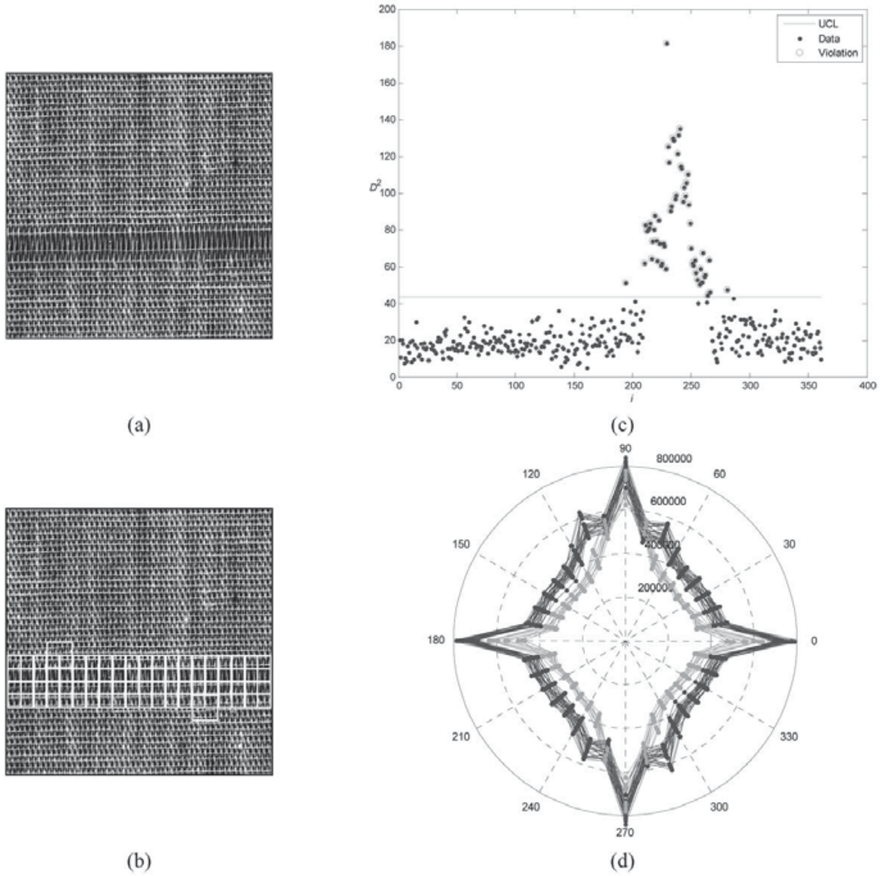


Fig. 2: (a) Defect in real structure, (b) results of detection algorithm, (c) plot of i-th test statistic, (d) polar plots in 10 step.

non-defective structure, whereas the shape of polar plots of defective structure differ significantly. More examples of defects in real structures after the application of detection algorithm can be seen in Figure 3, namely (a) foreign body, (b) double pick, (c) warp yarn defect, (d) snarl, (e) abrasion mark, (f) broken warp yarn.

It will be reasonable to devise an optimized method, which defines appropriate parameters for a given structure in terms of size of a sliding window. Figure 4(b)-(l) displays result of applied algorithm for detection of irregular weft density with various sizes of sliding windows.

5 Hardware

The algorithm that we talked about so far, was developed inside of Matlab using static images for purposes of fine tuning and testing. However, any algorithm that performs well in laboratory conditions may fail easily when applied in an industrial environment. For that reason we decided to build a laboratory device that would imitate production conditions by acquiring an image of moving fabric and applying the algorithms on-line. The experimental machine consists of aluminium frame, DC motor, LED illumination and a line scan camera. It's intended for repeated winding of endless strap of fabric, and thus to represent the behaviour of continuous process.

The apparatus is formed by a modular aluminium frame. A strap of a fabric can be up to $50cm$ wide

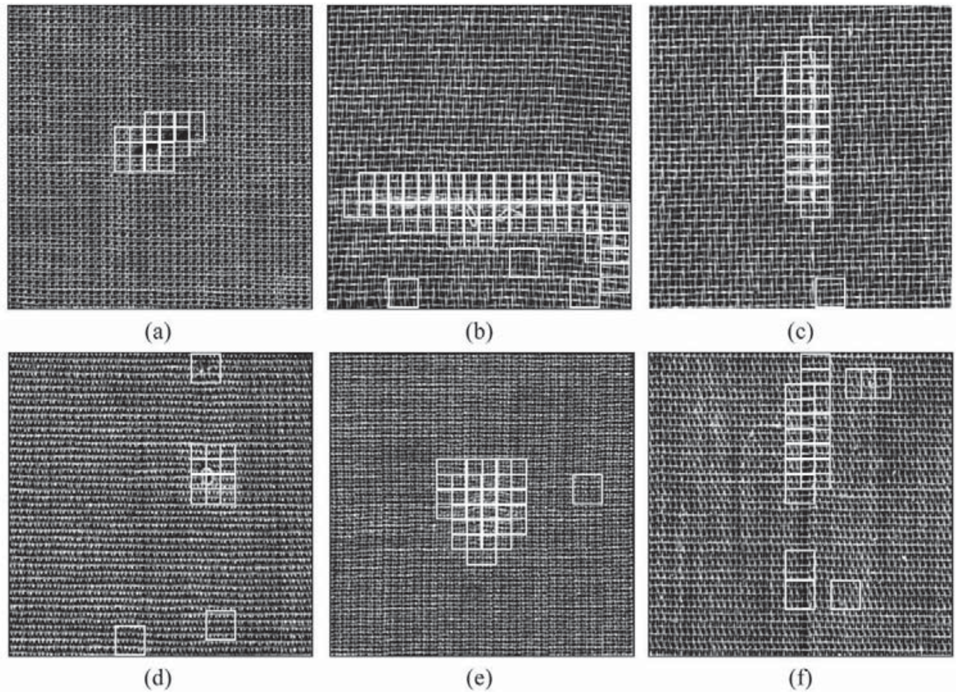


Fig. 3: Results of detection algorithm in real structures.

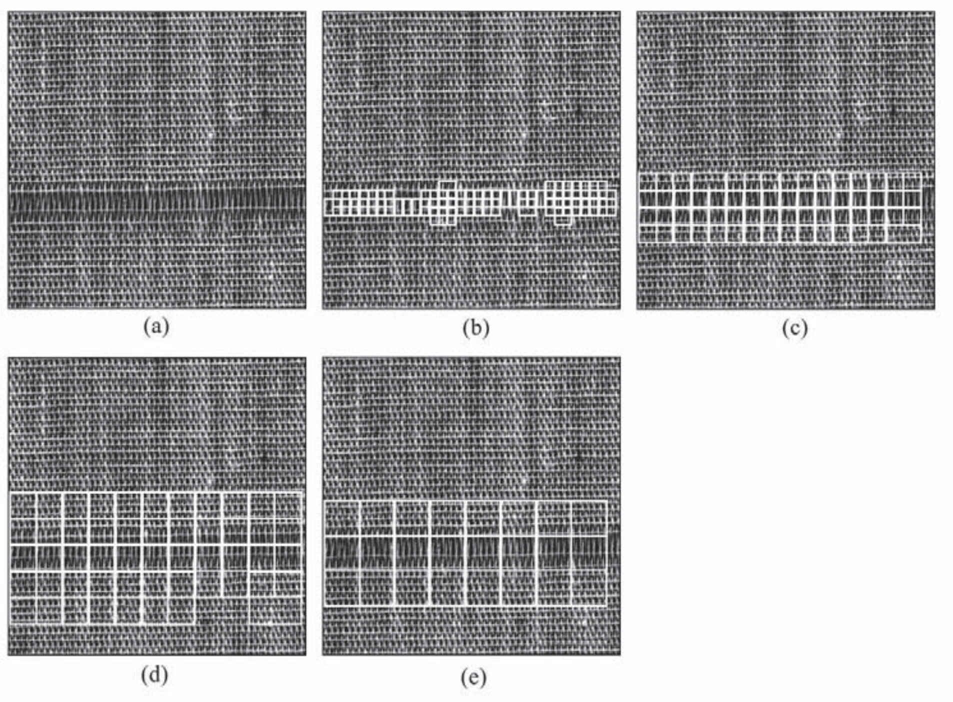
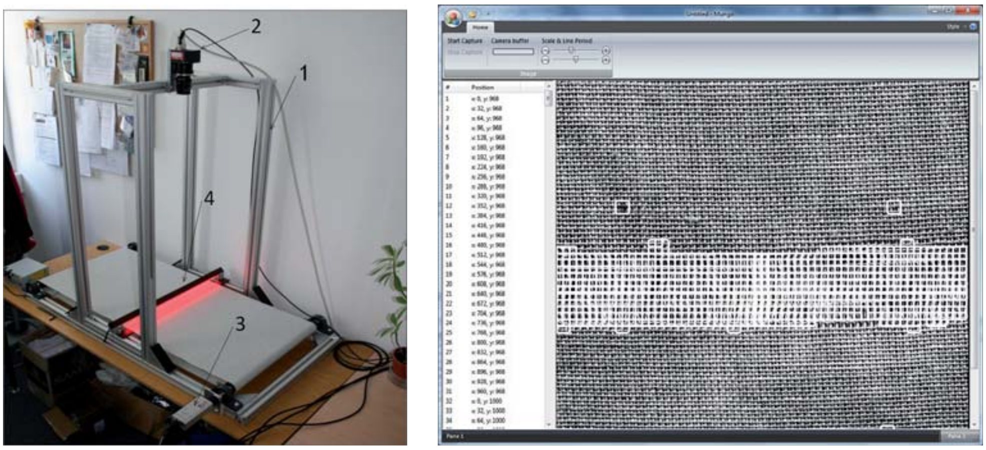


Fig. 4: Results of detection algorithm in real structures with different size of sliding window, (b) 30, (c) 60, (d) 90, (e) 120 pixels.

and over $2m$ long. There is a roller on each side that keeps the fabric straight. Thanks to the modular design of the frame, replacing the strap is quite easy, so various types of fabrics can be observed without too much effort. One major property of such design has its advantage that turning this laboratory device into industrial equipment consist only in mounting the camera on top of current inspection tables in the factory. No other modification would be necessary.



(a) (b)

Fig. 5: Laboratory device: (a) assembly; 1-frame, 2-line scan camera, 3-DC motor, 4-light array, (b) Application window.

One of the roller is driven by fully programmable *Maxon MCD EPOS 60W* motor. We use the cycle count property to track current position of the strap. The information about location of a defect is especially important for the serviceman who can make the appropriate correction short after the process has run out of control.

Image acquisition is performed using the monochrome *Basler L401k* line scan camera. It's line resolution is $4080px$, so that *8* pixels cover $1mm$ of fabric. Maximum line frequency $7.2kHz$ yields the theoretical top speed of about $46m/min$ with current optics and overall setup. However, real winding speed is limited by lightning conditions, fabric properties and mostly, by the complexity of data processing, rather than by technical parameters of each of hardware component. Camera's exposition time, line period, gain control and many other properties are exposed to the application and therefore can be modified on demand at runtime.

Although the on-line control has continuous nature, we have to divide the process into discrete portions by acquiring image into circular buffer. This concept comply with working principle of line scan cameras. By using line scan camera, one gets just a single row of the whole image at a time. In order to get the final image, subsequent rows need to be aligned into 2D array from capturing buffer. Ones we have a portion of a fabric acquired, we can run the image processing and analysis stage. Although this principle may involve serial processing, which would lead to serious problems in on-line control, there is a way not to waste the available computing resources, as described in Fig. 6. The image acquisition stage takes long time to complete. Specifically it takes image's *vertical resolution* multiplied by camera's *line period* seconds. Serial program would wait for that time idling and then, as the image buffer gets filled by data, it would perform the analysis. But the image acquisition would be forced to wait during analysis stage while the motor would need to stop as well. If the movement did not stop, the application would leave some part of fabric undetected. There is relatively easy solution to this particular problem that splits an acquisition and a processing into separate tasks and allows them to run in parallel.

6 Software

From the software perspective, we develop a standard *Windows MFC* application. There have been a lot of approaches to implement an automatic machines for control of quality characteristics in fabric. Despite these attempts, most implementations are either too simple and week or extremely expensive. Algorithm that is based on Fourier transform takes a lot of time to complete, so one could say that it's not much suitable for on-line processing. Anyway we see this approach robust and promising enough. The programming language we use is purely native *Visual C++* that executes much faster than interpreted *Matlab* code. There is also a user interface that inherits from *Windows 7 Ribbon* design which allows quick and intuitive control over the on-line quality control process. The client area of the application's window is divided into two panes which logically relate to each other. There is a list of detected defect in the left side. Each item in this list contains an information about defect location and size. These items are references to the fabric preview pane on the right side of the window (Figure **??**). Here a user can see the image of the textile together with visually highlighted defects. The application takes care about the control of the two major devices - motor and camera. Since the camera is line scan, the velocity and the line period has to be synchronized carefully in order to get undistorted image. The *OpenCV* library is used widely for image manipulation, processing and matrix operations.

Our aim is to produce cheap and commonly available, yet powerful equipment for quality control in the factory of any size, so we build the system using standard PC. Despite of availability and low cost of these machines, their powerful processors come equipped with at least two or four computational cores these days. Our algorithm for defect detection is based on spectral analysis in such a way that the whole image is divided into mutually independent sub-windows. We find the 2D Fourier spectrum inside each of these separate parts and by summing the frequency components in different directions we get a vector of desired characteristics. Then, we estimate the Mahalonobis distance of these characteristics from the reference vector and consider the value as a measure of structure irregularity. Since all the computations within every window are mutually exclusive from other windows, it allows to run the computation in different locations concurrently. Although parallel programming is much more challenging than development of a traditional serial program, well designed algorithm is able to fully extract the computational power of multi core processor. We have obtained a linear speed up with respect to increasing number of available processor cores. *Intel Threading Building Blocks* templates were used for writing the parallel

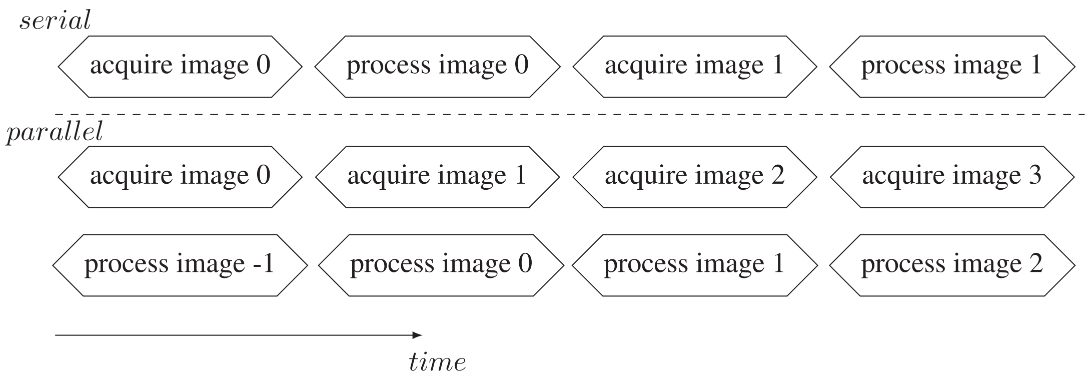


Fig. 6: Image acquisition and analysis cycle.

algorithm that can check $1m^2$ in about 1.5 second so far, running on *Core 2 Quad* processor.

7 Conclusion

Building a system of automatic visual quality control, that would support or even replace the quality control provided by human observation, is a complex problem that still provide enough topics for research. Although there are suitable control systems for paper, wood, steel and drug production industry, observation and reliable defect detection systems for textiles are still quite rare. There are two major aspects that make the inspection difficult for textiles. The first we mention lies in wide diversity of textile fabrics in terms of weaving and printing patterns. The products itself is of inhomogeneous structure that tends to tilt, stretch, etc. The algorithm has to be robust against the mistakes that can arise from such diversity. Together with robustness there comes complexity that affects the speed of execution, which is crucial in on-line quality control.

In our work we have implemented own algorithm for defect detection based on Fourier analysis. The algorithm was tested with woven fabrics that proved the algorithm to be highly sensitive to random irregularity in periodic structure. We also build a prototype machine that allows us to apply new algorithm under real conditions.

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References

[1] Tunak, M., Linka, A. Directional Defects in Fabrics. *Research Journal of Textiles and Apparel*, 2008, Vol.12, No.2, pp.13-22.

[2] Gonzales, R.C., Woods, R.E. *Digital Image Processing*, 2002, 2nd edition, Prentice-Hall.

[3] Tunak, M., Linka, A. Analysis of Planar Anisotropy of Fibre Systems by using 2D Fourier Transform. *Fibres & Textiles in Eastern Europe*, 2007, Vol.15, No.5-6 (64-65), pp.86-90.

[4] Bersimis, S., Psarakis, S., Panaretos, J. Multivariate Statistical Process Control Charts: An Overview. *Quality and Reliability Engineering International*, 2007, Vol.23, No.5, pp.517-543.

[5] Zamba, K.D., Hawkins, D.M. A Multivariate Change-Point Model for Statistical Process Control. *Technometrics*, 2006, Vol.48, No.4, pp.539-549.

[6] Bradski G., Kaehler, A. *Learning OpenCV*, 2008, 1st edition, O'reilly

[7] Reinders, J. *Intel Threading Building Blocks*, 2008, 1st edition, O'reilly